Simplifying Building Energy Performance Models to support an Integrated Design workflow

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Abstract. Detailed building performance simulation (BPS) is suited for verification of a design. Increasing needs to develop net-zero energy buildings, demands for passive, active and renewable energy design strategies to be aligned from the early design stage. This gives rise to simplified Building Performance Simulation (BPS) to be integrated at early design stage. This paper aims to identify the required BPS model level of detail with minimum error using parametric simulation models and Design of Experiments (DoE). Results indicates oversimplification in occupancy can produce huge error percentage of the simplified BPS model compared to detailed BPS model; followed by HVAC system, building form and so on.

1. Introduction

European Union is striving to achieve net-zero energy building by 2018 for offices and 2020 for residential buildings (Kreinera, Passera and Wallbaumb, 2015). The challenge in developing buildings with these sustainability requirements is that design elements cannot be directly associated with the requirements; it is the result of interactions between various design elements, local weather conditions, human behavior and so on (Weck, Roos and Magee, 2011).

The current design and development process equals more a linear process than an integrated process (Negendahl, 2015). Design information exchange takes place only for finalized or updated design (British Standard Institution, 2007). This situation limits the number of design options evaluated at early design stages. However, at these stages, chief decisions are made concerning the performance of the design. Therefore, a holistic approach is preferred, as it provides insight on interactions with other stakeholders and design element; such an approach allows to weigh all the pros and cons of a design decision (Kreinera, Passera and Wallbaumb, 2015). The term holistic approach refers to making decisions by considering both architectural and engineering design elements.

Technology for informed decisions is available: The design process uses Building Performance Simulation (BPS), which provides insight in performance of various design variants; Building Information Modelling (BIM) allows to share geometric and technical data with all stakeholders. The application of BPS causes modelling effort and computational load with respective delays – a fact that is aggravated by many variants or the systematic design space exploration (DSE). Common data formats like gbXML, IFC and visual programming languages like Dynamo enables easy data exchange between BIM and BPS facilitating the reduction of BPS modelling effort. Although BIM has the potential to ease the BPS modelling process, its application in early design stage is limited (Negendahl, 2015). Furthermore, it does not reduce time for detailed performance model definition as well as computation.

Simplified BPS models can reduce delay-causing efforts. Such models directly model dependency on chief design parameters and variables, such as occupancy, HVAC systems, lighting systems, building form, window to wall ratio, and material properties etc. However, depending on the kind of simplification, such models generate results that may or may not coincide with a detailed BPS model potentially steering the design in a wrong direction. This risk poses the question “What is the minimum required level of detail for BPS model’s to predict energy with accuracies similar to a detailed BPS model?”

This paper examines the required level of detail for a simplified BPS model to predict energy with sufficient accuracy but adequate effort and proposes an alternative metamodeling method for pure simplification of physical BPS. Depending on the metamodel implementation strategy, these models could become complimentary or competitive to early stage BPS models which is discussed further in the conclusion section.

2. Conceptual analysis

Early stage building design process

To determine, examine and propose possible model simplifications, it is necessary to know about the available information at early design stages. RIBA Plan of work 2013 and AIA outline the objectives of design stages and BIM model element’s Level of Development (LOD) (RIBA, 2013, Hamedani and Smith, 2015). Based on the definitions from RIBA and AIA, we transfer the LOD concept to the whole building as “component” and divide early design it into two stages, namely, preparation stage with LOD 100 and conceptual design stage with LOD 200:

Preparation stage with LOD 100	*Concept design with LOD 200*
- Quality objectives - Project outcomes - Sustainability aspiration - Budget - Other constrains	- Architectural design - Structural design - Building services systems and outline specifications - Cost

The increase of LOD relates the accumulation of information by planning activity and inherent decision making. Key design decisions taken at LOD 100 and 200 have major impact on the performance of the actual building (Piccoa, Lollini and Marengo, 2014).

Performance gap and prediction gap

The difference between the monitored energy consumption and the predicted energy demand is referred as performance gap (Niu, Pan and Zhao, 2015). Reasons for performance gap are erroneous design assumptions, fundamental errors within modelling tools and their application as well as deviations and misbehaviour in building operation. Design assumptions include simplification of models and idealistic design inputs (Menezesa et al., 2012).

Early stage usually simplifies analysis and typically focuses on either architectural design elements (Hamedani and Smith, 2015) or building systems (Seo, Ooka, Kim, & Nam, 2014). Depending on focus of the analysis model, different areas of BPS model are simplified. In analogy, we call the potential error of model simplification compared to a detailed BPS model in this paper as ‘prediction gap’.

Hierarchy of a building's energy performance and BPS

Energy performance of a building depends on building characteristics, building systems and building operation (Kalkman, 2012). Figure 1 shows the layers of a detailed BPS model that contribute to the building energy predictions. The more layer a BPS model has the more detailed it is and vice versa. The number of layers in each BPS model area is referred as its level of detail (please note the distinction to level of development, LOD). Realistic representation of these BPS model areas reduces the performance gap (Murphy and Castleton, 2015, Beltrami et al., 2015).

When areas of building characteristics are dynamic in nature, like the use of smart window or movable overhangs these areas are moved to building systems and operations levels. The reason is that these design elements form a system, whose performance not only depends on interaction between design elements buts also other stakeholders. Therefore, selecting a suitable simplification method becomes a key factor. Level of details is reduced by considering higher hierarchy levels within the model resulting in a simple BPS model with less layers. The impact of an area, which is later in the paper determined, is key information for deciding about this simplification. Simplification is done using a simple BPS tool or using detailed BPS tool with assumptions on unknown parameters. Hence, knowing the required minimum level of detail for a holistic BPS model helps in making effective choice between a simple or detailed tool.

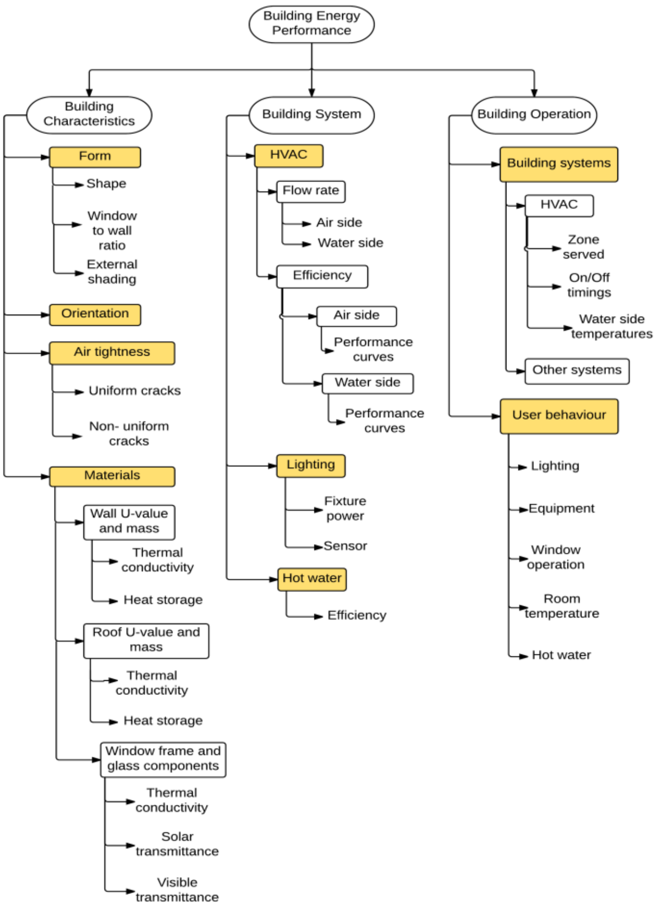


Figure 1: Hierarchy of building energy performance

Design of Experiments (DoE)

In this paper, DoE is used to identify the required level of detail for a BPS model. Typically, application of DoE serves to get insights on the variables, that have the most impact on the performance with a minimum number of experiments, i.e., simulations in this case (Antony, 2003). DoE is typically used because it provides information about all main effects and interactions. Main effects are the individual effects of a variable on the performance while interactions are the effects of a variable on performance depending on the state of another variable.

Plackett-Burman (P-B) design, which is a fractional factorial design technique, is applied to evaluate the required level of detail for a simplified BPS model. This design technique is suitable this study, as it can identify the parameters which have the highest impact in a process with minimum experiments. This means only main effects are evaluated through this technique. The P-B design is based on Hadamard matrices which has experimental runs in multiples of four. P-B design matrix indicates the variations of a parameter in each experiment (Antony, 2003). Variation of a parameter is defined as the different parameter values used in each experiment. Variations in this study refers to simple and detailed modelling methods.

Metamodelling simulation

The chosen metamodelling approach provides a black box surrogate model to approximate expensive simulation experiments. Forrester et al. (2008) gave a general introduction on the use of metamodelling in engineering. Simpson et al. (2001) provided a comparison of such techniques. Simpson et al. (2001) and Jin et al. (2001) examined the influence of design types and size for computer experiments and different methods of metamodelling. Bletzinger and Lähr (2006) applied RSM in the context of an agent-based decision environment. Chlela et al. (2009) and Jaffal et al. (2009) applied traditional RSM to the setup of a metamodel for the thermal performance of a building. Gholap and Khan (2007) used metamodelling for component-level optimization of a heat exchanger in a refrigerator. They built a component metamodel for optimization but did not use it further for design and simulation. Furthermore, a metamodel traces relationships observed within the reference data (Liu, Huang and Stouffs, 2015). Metamodels developed with specific datasets makes them applicable in limited situations only; this makes it complimentary to BPS. In contrary, the hypothesis of this paper is that models developed with diverse datasets could result in generic metamodels which could substitute BPS in certain situations and makes them competitive with BPS.

3. Identifying the required level of detail

Objective of the experiments

The objective of the experiment is to identify level of detail for a simplified BPS models. A P-B design with 16 runs is performed in IES VE software. The BPS model represents a schools located in an urban environment in Abu Dhabi. Please note that the DoE outcomes for other weather files can be different and is not dealt in this paper.

Variations of the level of detail

Table 1 shows the variation of BPS model's level of details. The P-B design matrix, generated through Matlab using the command "hadamard", consists of the combination of variations within the BPS model for each experiment, i.e., simulation run.

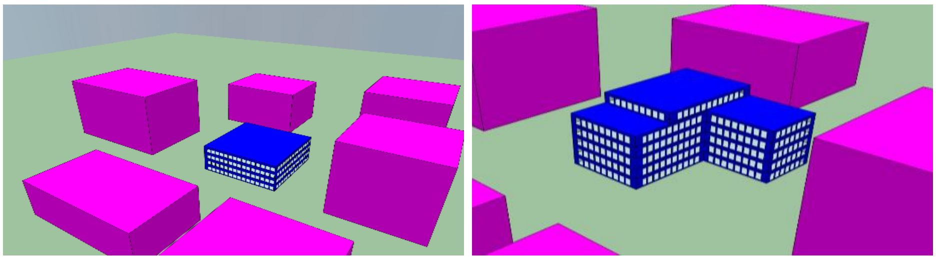


Figure 2: IES VE models

The following variations are considered:

1. *The building form* at – 1 and +1 levels have the same built-up area. The complexity is increased by changing the shape of the building to better represent the real form.
2. *Variations for orientation, shading and airtightness* do not have the same values at -1 and +1. These parameters are present to induce noise in the experiments.
3. The *thermal mass* modelled for walls at -1 and + 1 levels are the same. However, the roof is modelled with two different thermal masses. This is done to observe possible errors in energy predictions with wrong assumption.
4. *Detailed occupancy* is modelled by creating rooms within the model and assigning three different profiles (see Figure 3) in an alternating manner varying occupancy and equipment load but not lighting. Lights are assumed to be turned on while the building is occupied.
5. *Simple HVAC system* is modelled by means of the Apache systems in IES VE and *detailed HVAC system* is modelled by means of Apache HVAC.
6. S*imple airtightness* is modelled with constant infiltration of 0.25 ACH and *detailed airtightness* is modelled by defining cracks in IES VE's MacroFlo module.

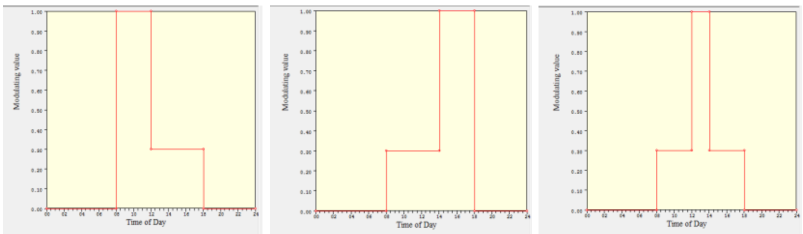


Figure 3: Occupancy and equipment usage profile

Table 1: Variations in BPS model's level of detail

BPS model areas	**Value**	**Variations in BPS model level of detail**	
		-1	**1**
Building form		Square	L-shape

Orientation		0	230
Shading		No shading	External fixed overhang
Window to wall ratio	40%	Single window	Multiple windows
Wall properties	0.32 W/m^2K and light weight	Single layer construction	Layer by layer construction
Roof properties	0.1 W/m^2K	Single layer construction (very light construction)	Layer by layer construction (light construction)
Windows properties	1.14 W/m^2K and 0.36 (g-value)	Single layer	Layer by layer
Airtightness		0.25 ACH	Crack length 7% of openable perimeter and crack flow coefficient of 0.150 l/(s m Pa^0.6)
Lighting	10 W/m^2	On/Off	Daylight sensor
HVAC	Chiller COP – 6.3 Boiler efficiency – 0.81	Peak and seasonal efficiencies	VAV-reheat with EWC chiller and HW boiler
Occupancy		8:00 to 18:00	3 profile for occupancy and equipment. Lighting operated between 8:00 to 18:00

Analysis results

The level of detail within a BPS model, which has the most impact on energy performance predictions are shown in Figure 4. It can be noted that level of detail for occupancy has the highest impact on the predicted building energy. This is followed by HVAC system, building form, lighting, airtightness and so on.

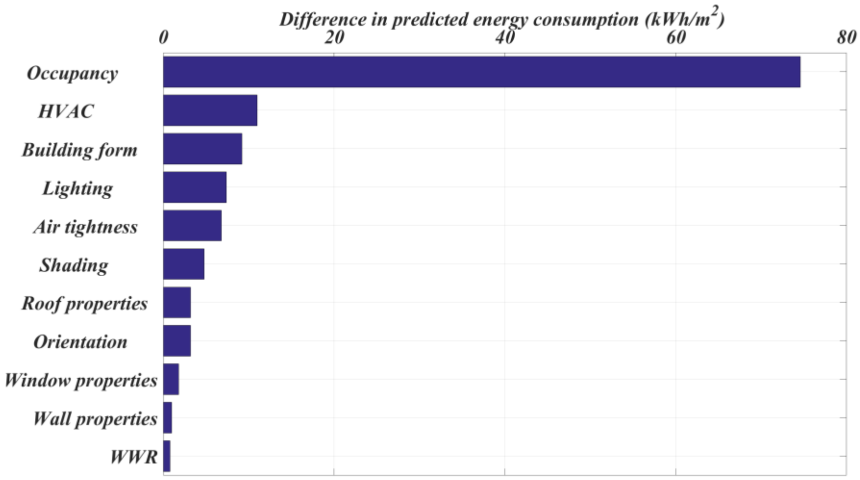


Figure 4 Pareto graph of effects for varying BPS model level of detail

Interpretation and discussion of results

In general, BPS model areas with high main effects require high level of detail. In contrast, low level of detail is sufficient for areas with low main effects.

Occupancy. The results indicates that wrong assumptions or over-simplification in occupancy will result in a high prediction error, which could lead to a wrong energy strategy. Therefore, modelling occupancy as detailed as possible is crucial. Some possibilities for occupant modelling are:

- Acquire occupancy related data from similar building in the region via platforms like CarbonBuzz.
- Use statistical methods to model occupancy and predict energy for various occupancy scenarios as suggested in CIBSE TM54.

HVAC system. Figure 5 shows the HVAC chiller efficiency used to calculate energy consumption with a detailed HVAC model. Colour of the points in Figure 5 shows the chiller COP varying between 4 to 13 under varying chiller load and ambient temperature. This illustrates that modelling only peak and seasonal efficiencies is not sufficient, as lot of data essential for accurate energy prediction is absent in an oversimplified HVAC model.

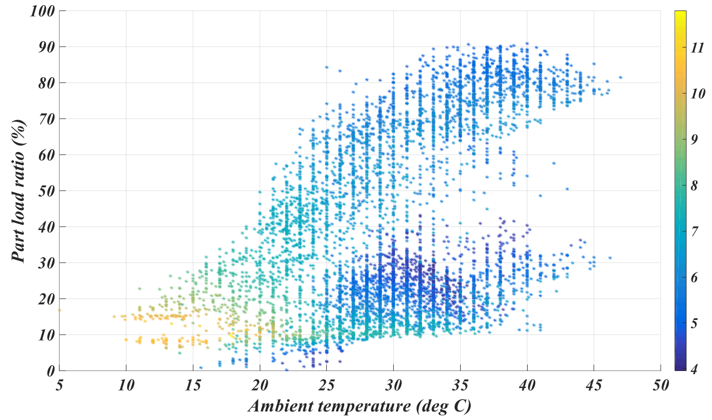


Figure 5: Chiller COP as a function of part load ratio (%) and ambient temperature (deg C)

Building form. Depending on the form and external neighbouring building shading, the solar radiation profile, i.e., amount of solar radiation on the building varies. This in turn has an impact on the buildings energy performance. Therefore, it is crucial to model various building form and urban area at early design stage rather than a simple box building.

Lighting. Lighting system design that uses daylighting dimming sensors requires to be modelled in detail. However, the impact of lighting design's level of detail may not be observed in locations where majority of the days are cloudy. Hence a simplified lighting model would be sufficient for these regions.

Material properties. In the study, roof material properties have more impact on accuracy than wall or window. This is the result of a difference in thermal mass in the roof material's level of detail. Therefore, it is important to capture thermal conductivity and heat storage capacity for wall and roof accurately. Modelling it through a single layer or layer by layer method has less impact on energy predictions. A similar observation is made for window properties. Capturing the solar heat gain value accurately is more important than the method of modelling. However, these methods may play more importance in predictions of other requirements.

Window to wall ratio. Modelling a simple window will be sufficient to predict energy accurately.

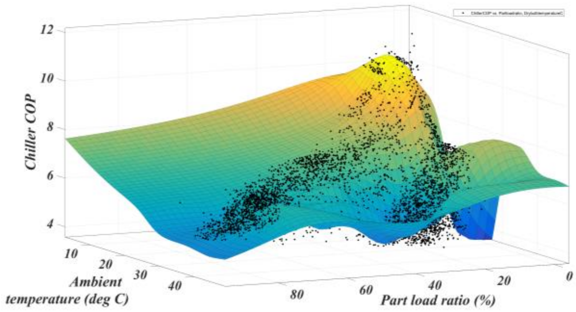
4. Simplification by metamodelling

Detailed models are not suitable for early design stage due to high simulation and development time. Furthermore, conventional detailed simulation approaches do not focus on the design parameters that are important in early design phases, e.g., window-to-wall ratio. Metamodels built on simulation results can be very beneficial in this situation. There are two different kinds of the application of metamodels to reduce the simulation time:

(1) to build metamodels for the whole simulation model;
(2) to develop meta-models of building components, which are integrated into other models, in our case the BPS model.

Whereas the first method focuses on the specific case, the second method has the potential to produce more general models. The aim of such general models is the reuse if the conditions match. Besides detailed BPS model, meta-models can also be generated based on measurement data.

Meta-models are models that imitate the behaviour of a physical simulation model or a real object based on measurement data. Figure 6 shows the surface generated through MATLAB's curve fitting tool with thin-plate spline interpolants method for the simulation results of the chiller shown in Figure 5. Thin-plate spline interpolation method fits a smooth surface over the available data-points which also extrapolates in a good manner. However, predicting values in extrapolated regions may be inaccurate. This surface can be used to predict the COP of the chiller for various chiller load and ambient temperature. For different chiller types or design COP, more data have to be generated and a further model needs to be fitted. Inputting these (or similar curves) efficiency into a BPS model to predict energy performance could reduce the prediction gap, when replacing peak and seasonal chiller COP. Figure 7 shows the proposed interaction between BPS and chiller metamodel. The first few simulation steps are called preconditioned simulation, where BPS model provides COP dependent on cooling load and ambient temperature for the metamodel. The resulting metamodel is then used to predict energy consumption during annual simulation. Once stability in this process is achieved, actual simulations begins.



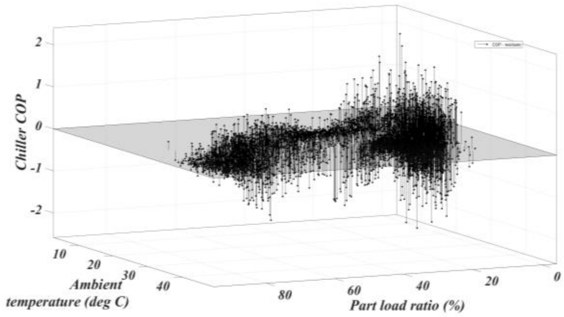


Figure 6: Interpolated surface model (top) and residuals plot (bottom) of chiller COP Vs Ambient temperature and part load ratio

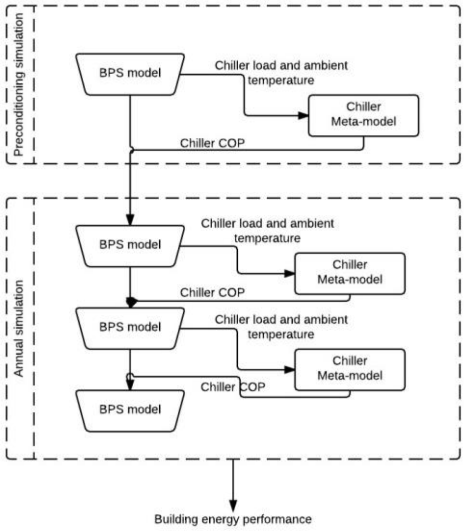


Figure 7 Integrating meta-modelling into BPS for model simplification

The effectiveness of this simplification method has to be researched further. Some possible advantages of this method are:

1. Generalized metamodels deliver the detailed performance of a component without tedious detailed modelling and simulation. However, one has to pay attention that the parameters are within the bounds of the model.
2. Modelling limitations of a BPS can be compensated by metamodels. For example, modelling capabilities of upcoming complex technologies like smart windows, organic solar cells or PCM are limited in most of the whole building simulation tool. Metamodels of these technologies can be integrated into BPS so that they can be evaluated in early design stage. Besides simulation-based metamodels, also empirical data from laboratory can be used.

Next steps in research are the implementation of the metamodel in a dynamic simulation environment and test its accuracy. Metamodels will be developed in such a way that the prediction error is low for new datasets, i.e., datasets different from the reference dataset. High prediction error on new datasets requires changes in the metamodel configuration or more reference data. Decision on modifying the metamodel or gathering more data will be made based on observations in the following graphs (1) prediction error vs dataset size (2) prediction error vs model complexity (Richert and Coelho, 2013).

5. Conclusion and discussion

Developing simple quick-responding BPS models for early design stages with low prediction gap is crucial in our mission to reduce the performance gap and effective development of net-zero energy building. This paper highlights the areas of BPS models, which requires high- and low level of detail. Enabling, early design stage BPS model simplification that caters to the requirements of both architects and engineers. A holistically simplified BPS model creates a common platform, upon which early-stage-design decisions on passive, active and renewable energy systems can be based and respective strategies are developed in synergy.

Integrating metamodel component, which captures all the interactions of a detailed BPS model area, within a simple BPS model could result in a model with low prediction gap. This arrangement also allows evaluation of innovative technologies or complex systems, which are typically difficult to model in simple BPS models. Metamodels that can be applied to a wide range of situation makes it competitive to detailed BPS models for early design stage. While metamodels developed for a specific case make it complementary to BPS.

The quality of inputs within the BPS model plays an import role in reducing the prediction and performance gaps. Quality here represents the closeness of these inputs towards reality or as-built conditions. Predication gap is minimized directly by the presented study. Whereas, performance gap is reduced indirectly: The knowledge about the impact of input parameters by the shown level-of-detail analysis allows to improve the quality of input parameters; the input quality is the main key to reduce the performance gap. Quality inputs could be obtained from databases like CarbonBuzz or by involving various stakeholders like occupants, building system supplier during early design stage for BPS models inputs.

Involving various stakeholders at early design stage results in a shift from a linear design process towards an integrated design process. This shift requires a platform and a structure to communicate information between different stakeholders. We expect future capabilities of BIM to facilitate such communication between design teams and other stakeholders. Increasing BIM capabilities could include integration of tool like life cycle analysis, BPS, etc into the BIM environment. Results from the BPS models can be communicated to various design teams and stakeholders via BIM, which can be used to steer design and information exchange. Information exchange stored within BIM can be used to trace a particular design decision as design progresses or during post-occupancy study.

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